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# A modeling framework for evaluating the drought resilience of a surface water supply system under non-stationarity

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ABSTRACT

The future resilience of water supply systems is unprecedentedly challenged by non-stationary processes, such as fast population growth and a changing climate. A thorough understanding of how these non-stationarities impact water supply resilience is vital to support sustainable decision making, particularly for large cities in arid and/or semi-arid regions. In this study, a novel modeling framework, which integrates hydrological processes and water management, was established over a representative water limited metropolitan area to evaluate the impacts of water availability and water demand on reservoir storage and water supply reliability. In this framework, climate change induced drought events were selected from statistically downscaled Coupled Model Intercomparison Project Phase 5 outputs under the Representative Concentration Pathway 8.5 scenario, while future water demand was estimated by the product of projected future population and per capita water use. Compared with the first half of the 21st century (2000–2049), reservoir storage and water supply reliability during the second half century (2050–2099) are projected to reduce by 16.1% and 14.2%, respectively. While both future multi-year droughts and population growth will lower water supply resilience, the uncertainty associated with future climate projection is larger than that associated with urbanization. To reduce the drought risks, a combination of mitigation strategies (e.g., additional conservation, integrating new water sources, and water use redistribution) was found to be the most efficient approach and can significantly improve water supply reliability by as much as 15.9%.

## 1. Introduction

Resilient water supply systems are critical for urban socio-economic development. To be classified as resilient, a water supply system should not respond precipitously to a major 'surprise' during its economic life (Fiering, 1982). Currently, most of the existing water infrastructures were designed with the assumption of stationarity—a belief that historical statistics can be applied to future decision making (Matthews et al., 2011; Koutsoyiannis & Montanari, 2015). However, this assumption is challenged by ongoing global environmental changes, such as climate change, population growth, and land use land cover (LULC) change (Milly et al., 2008; Gao & Bryan, 2017; Zhao et al., 2016a). Subsequently, the sustainability of our water resources management systems is at unprecedented risk (Dovers & Handmer, 1992; Hirsch, 2011).

To manage a water supply system sustainably, the key is to balance water availability with water demand. Yet both availability and demand are susceptible to non-stationarity. On the availability side, there are multiple non-stationary factors such as climate change, flow regulation, LULC change, and increasing groundwater withdrawals (Kundzewicz et al., 2008; Zhang et al., 2015; McDonald et al., 2014; Barlow & Leake, 2012). Among these, climate change induced precipitation alteration is expected to result in the largest impact on water availability (Milly et al., 2005; Schewe et al., 2014). In the past several decades, both observations and model simulations have shown increasing aridity trends across the globe due to the changing climate (Dai, 2013). Moreover, with enhanced evapotranspiration loss due to increasing global temperatures, droughts are likely to be more severe with longer duration (Parry, 2007). On the demand side, both the net growth and migration of population challenge the stationarity assumption. Global freshwater consumption has increased nearly six-fold from 1900 to 1995 as a result of population growth (Shiklomanov, 1999). Specifically, regional water demand has surged due to urbanization (population redistribution) for many regions in the world. How

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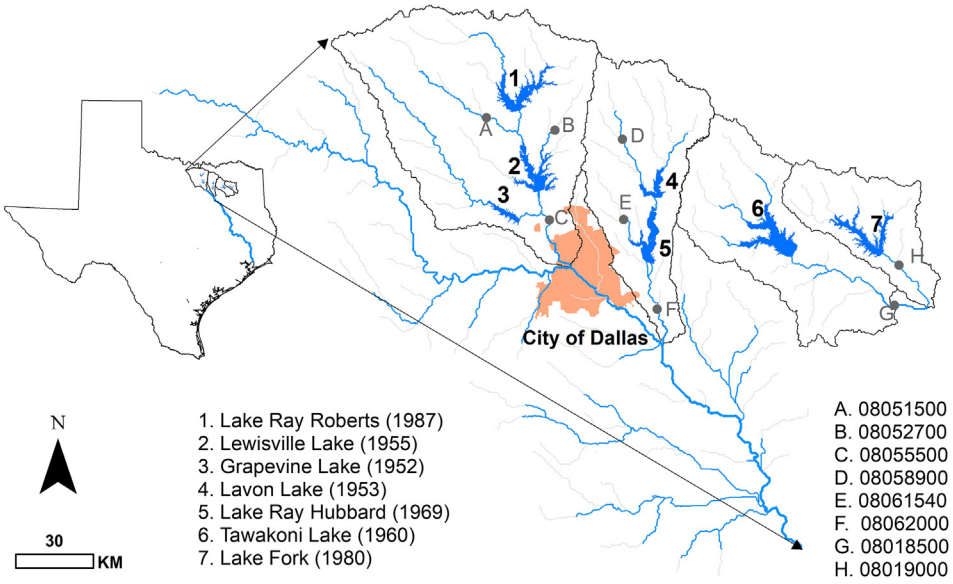


**Fig. 1.** Simulated watersheds which provide inflows to the Dallas water source reservoirs. Both the reservoirs and USGS streamflow gauges used for model calibration and validation are indicated.

to best provide sufficient water for the world's growing cities has become the most difficult and urgent problem for water management (House-Peters & Chang, 2011). Results from McDonald et al. (2011) suggest that there were 150 million people in city areas suffering from perennial water shortage in the year 2000. This number will increase to 1 billion by 2050 due to population growth.

However, evaluating future water supply resilience in a non-stationary fashion is critically difficult, primarily due to three challenges. The first challenge is that the current modeling tools are inadequate to represent the dynamic feedback between hydrologic variabilities and water management decisions. Currently, natural hydrological processes and water management activities are modeled in a separate or not-fully-integrated manner (Muttiah & Wurbs, 2002; Portland Water Bureau, 2002; O'Hara & Georgakakos, 2008; Matonse et al., 2013). Despite in-depth thoughts and processes existing in both types of models (i.e., natural rainfall-runoff versus operational reservoir management models), the connections were usually loosely made through a few selected surface water controlling points. This simplification would inevitably lead to inaccurate simulation of water availability and demand, as well as their dynamic two-way interactions (Zhao et al., 2016b). A few models—such as the Hydrological Simulation Program-Fortran (HSPF; Bicknell et al., 2001) model and the Soil and Water Assessment Tool (SWAT; Arnold et al., 2012)—are capable of addressing processes on both sides. However, such models are usually lumped/semi-lumped and are insufficient to represent dynamic features such as enhanced open water evaporation through reservoirs. Therefore, full integration of the spatially distributed hydrological processes with water management activities should be prioritized for model development and employment.

The second challenge is that droughts are intrinsically difficult to predict—especially in the long-term future (given the large uncertainties). Considering its low probability and our limited observational records, future drought scenarios that fully rely on historical observations (Frick et al., 1990; Bekele & Knapp, 2010) may underestimate the severity and trend of future droughts in the context of notable thermodynamical and dynamical global changes (Emori & Brown, 2005; Seager et al., 2010). Even for the historical period, there are still disagreements about the trends of global drought (Dai, 2013; Sheffield et al., 2012). In order to evaluate water supply resilience more reliably, there is a need to utilize ensemble-based future drought projections to support our decision making.

The third challenge is that both availability and demand estimates involve large uncertainties, which add another layer of complexity to the water supply resilience evaluation. Yet uncertainty analysis is important for policy makers who make important decisions under an environment of risk. Thus, quantification of uncertainties associated with non-stationarities is critical for water resilience evaluation.

To our knowledge, there have been very few studies that focus on water supply resilience under multi-year droughts using fully distributed hydrological models dynamically coupled with water management systems (Amarasinghe et al., 2016; Watts et al., 2012; Collet et al., 2015). Most of these studies mainly tested the system resilience based on historical or artificially designed droughts—and not on the expected future droughts derived from state-of-the-art climate models. Therefore, in this study we used a novel modeling framework which integrates hydrological processes and water management decisions (Zhao et al., 2016b) to overcome these limitations and dynamically evaluated water supply resilience under the impacts of two most significant sources of non-stationarities—potential multi-year droughts, and the growing demand from an increasing population. We specifically want to answer three scientific questions:

1) How do sources of non-stationarities from both availability, especially under multi-year droughts, and demand influence the resilience of a water supply system?
2) How do uncertainties associated with these sources of non-stationarities compare, and which side (i.e., availability or demand) is dominant?
3) What are the possible mitigation strategies to improve water supply resilience?

In this paper, we use a case study to demonstrate a holistic approach for evaluating the future water resilience of large cities under an environment of non-stationarity by bridging the gap between hydrological modeling, water management practices, climate change studies, and population/demographic projections. In Section 2, the selected study area, the City of Dallas, is introduced. The detailed methodology is explained in Section 3. In Section 4, the model calibration/validation results are first demonstrated, and then the future water supply and demand are compared and analyzed under various drought scenarios (with the goal of answering the aforementioned scientific questions). Section 5 discusses the conclusions and the general applicability of this

approach.

## 2. Study area

The City of Dallas in Texas (Fig. 1) was selected as our pilot study area to demonstrate the modeling framework, which is applicable to any surface water dominated urban water supply system. Dallas is the ninth largest city in the U.S. in terms of population size. From 1950 to 2010, Dallas has experienced very fast urbanization, both inside of the city boundaries and in the surrounding suburbs. Within the city alone, the population has increased from 0.43 million to 1.20 million during this time period. With this rapid urbanization process, the capability of existing water systems to handle increasing future demand becomes a main concern for water resources planners in the area.

Because of the limited groundwater resources, the water supply of Dallas fully depends on surface water, which is highly variable both seasonally and inter-annually. During the severe 1950s statewide drought, Dallas' municipal water supply was fully depleted. The city's major water source, Lake Dallas, only had a capacity of $2.39 \times 10^8\ m^3$. This was quickly depleted once the drought started, and the city had to purchase salty water from the distant Red River to survive. Because of the severe water stress induced by this drought, policy makers launched extensive reservoir construction projects to reduce future drought impacts on the city (Fig. 1). In the Trinity River Basin, four lakes were gradually constructed—Grapevine Lake (impounded in 1952), Lavon Lake (1953), Lake Ray Hubbard (1969), and Ray Roberts Lake (1987). Lake Dallas was also expanded to $5.38 \times 10^8\ m^3$ and renamed as Lewisville Lake (1955). In addition, the City of Dallas contracted with the Sabine River Authority for additional water supply from Lake Tawakoni (1960) and Lake Fork (1980). In 2010, these seven multi-purpose reservoirs were capable of providing about $1.89 \times 10^6\ m^3/d$ for Dallas. Dallas Water Utilities (DWU) is responsible for the municipal water supply for the city, and for 27 wholesale customer cities. The total population served by DWU from the connected reservoirs was 2.40 million in 2010, with a total water demand of $1.63 \times 10^6\ m^3/d$ (Texas Commission on Environmental Quality, 2017).

Even though the combined capacity of these seven reservoirs is sufficient to satisfy Dallas water demand at $1.63 \times 10^6\ m^3/d$, the real-time reservoir storage varies considerably due to climate variability and other factors. How this water supply system will respond in a non-stationary environment is an unsolved question for the policy makers. Climate change, and the associated increase in severity and frequency of extreme events that affect future water availability, are increasing this challenge (Venkataraman et al., 2016). Meanwhile, the city will also be stressed by increasing water demand from population growth, which will be exacerbated by decreasing water availability due to more frequent drought conditions. Therefore, to better support policy making for the sustainable development of the City of Dallas, it is essential to quantify the resilience of the water supply system in the context of demographic growth and future potential droughts.

## 3. Methodology

### 3.1. Drought quantification under future climate conditions

In a changing climate, drought projections that only use historical data are no longer appropriate for representing the non-stationary system. In the past decades, general circulation models (GCMs) have been substantially improved with regard to both model algorithms and spatiotemporal resolutions (IPCC et al., 2013). Even though these physically based models provide quite different projections for the future, they offer a range of possible conditions by simulating the evolution of the physical processes. Therefore, they are widely used for drought evaluation under a non-stationary climate (Ghosh & Mujumdar, 2007; Touma et al., 2015).

There are several drought indexes that are commonly used for quantification of different drought types (e.g., atmospheric, hydrological, and agricultural). In this study, we employed the widely used Palmer Drought Severity Index (PDSI; Palmer, 1965) to quantify meteorological drought. As it uses the Available Water Content (AWC) of the soil to calculate other basic hydrologic terms (such as potential evapotranspiration (PET), potential runoff, soil recharge, and soil loss), it is capable of accurately capturing the drought characteristics impacting the surface water-based supply system of Dallas. For the PET calculation, currently there are several algorithms available (Thornthwaite, 1948, Hamon, 1960, Priestley and Taylor, 1972, Monteith, 1965, and others). Among these approaches, the Penman-Monteith approach (Monteith, 1965) is considered the most accurate because it uses precipitation, radiative forcing, wind speed, and humidity data to estimate PET (instead of only using temperature, for example, such as the Thornthwaite's method). The PDSI generated from Penman-Monteith PET calculations (PDSI-PM) has shown to be a more accurate representation of historical droughts than the more commonly used PDSI from Thornthwaite's PET method (Sheffield et al., 2012). From this perspective, PDSI-PM is more physically based and thus more appropriate in this case study than other indexes (such as the standardized precipitation index and the aridity index) (Dai, 2011). Thus, in this study, we employed PDSI-PM to better represent the drought processes.

Statistically downscaled meteorological forcings were adopted from the Downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) Climate and Hydrology Projections (Reclamation, 2013). However, not all GCMs from CMIP5 are suitable for application on any given target watershed (Chiew et al., 2009). By comparing the cumulative probabilities between the GCM-based PDSI-PM and the observation-based PDSI-PM during the historical period (1950–1999), 8 models (out of 19) were selected to provide future drought scenarios given their abilities to better represent the historical drought patterns (Supporting Information). Representative Concentration Pathway (RCP) 8.5 was selected as an example to demonstrate the drought quantification framework. Compared with other RCPs, RCP 8.5 offers a larger uncertainty range for testing the water supply resilience (the comparison between RCP4.5 and RCP8.5 is in the Supporting Information).

Drought quantification was conducted in two steps. First, PDSI-PM time series were calculated for each of the 8 GCMs. In order to choose the drought events of interest from the time series, a threshold (under which droughts are defined) was applied. In the original study conducted by Palmer (1965), −0.50 was used as a threshold based on a case study in central Iowa and Kansas. However, this value was rather arbitrarily selected and was not identified based on physical meaning (Alley 1984). Thus, a location specific PDSI-PM threshold is more appropriate for quantifying the beginning and ending of droughts (Burke et al. 2006; Ryu et al. 2014; Svoboda et al. 2015). In this study, we used the 20th percentile of historical PDSI-PM values as the threshold. Second, the most severe droughts were selected based on the cumulative PDSI-PM deficit for two future periods (Fig. 2 and Table 1). Period 1 is from 2000 to 2049, and Period 2 is from 2050 to 2099. We used the most severe droughts because they can better test the resilience of the water supply system, and therefore provide the worst possible situation (that can, in turn, help to adjust current policy).

Both Fig. 2 and Table 1 suggested significant non-stationarity in future water availability (introduced by prolonged droughts). From Period 1 to Period 2, the average drought duration has increased from 23 months to 36 months. Similarly, the drought severity, which is the cumulative PDSI-PM deficit, has increased from 36.5 to 84.1. Specifically, the most severe drought in Period 2 lasts for 61 months, resulting in a severity of 181.3.

### 3.2. Water demand under growing population

Water demand is the total amount of water needed by consumers.

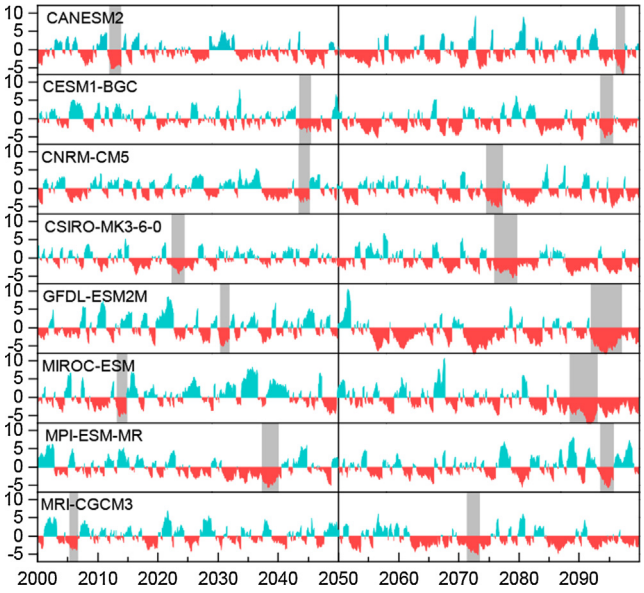


**Fig. 2.** PDSI-PM time series from 8 GCMs in the RCP8.5 scenario. Grey shaded areas represent the most severe droughts based on a threshold of −1.924 (i.e., the 20th percentile of historical PDSI-PM) for Period 1 and Period 2.

To ensure the regular operations of a society, the water demand should be satisfied regardless of the external circumstances (e.g. flood or drought). However, there are a number of factors that can influence water demand, especially with respect to population growth and changes in water use per capita per day (WUPCD). Some other influential factors include economic activities, LULC change, water price, water leakage, water recycling, and others.

Since water demand is affected by many factors (each with associated uncertainties), its future projection is usually limited. For example, many climate studies use fixed values for these parameters and provide multiple (or even single) scenarios for the water demand (Wu et al., 2015; Ranatunga et al., 2014; Laghari et al., 2012). Furthermore, there are no quantified uncertainties associated with the demand scenarios. This dramatically restricts the application of these studies in the policy making process.

Historically, the city planners have been managing the water supply reservoirs as a system. Therefore, we made future projections based on the total water use from these 7 reservoirs (instead of making an individual projection for each one of them). Using the 2007–2011 water use data as the initial condition, a Monte-Carlo simulation was utilized to estimate future water demand in order to obtain the most likely demand values with their associated confidence intervals. It is assumed that the future water demand is primarily affected by population and WUPCD. For population, we defined an increase rate, $r_N$, which follows a normal distribution – an approach used in many studies (Hone, 1999; Nam & Reilly, 2013). The average population increase rate ($r_N$,) is set to 1.32%/yr for the City of Dallas according to the Dallas City Council (2014). With respect to WUPCD, there is a decreasing trend due to technology improvement and policy intervention over the past 30 years (Texas Water Development Board [TWDB], 2016). In 2011, the average WUPCD for Dallas was about 745 L, which has reduced by 235 L since 2000. However, compared with other US cities – such as New York City, which currently has a WUPCD of 450 L – there is a large potential to further reduce the Dallas water demand per capita. Thus, TWDB projected a continuous reduction of WUPCD for Dallas. The average decrease rate is 0.45%/yr (TWDB, 2016). The decreasing rate of WUPCD, $r_U$, is also assumed to follow a normal distribution to account for possible uncertainties (Billings & Jones, 2011). The parameters of these two normal distributions were estimated according to the Dallas City Council (2014). Other factors such as water supply leakage and rainfall harvest – which are considered to be water conservation practices (see Section 4.3) –are not represented in Eq. (1).

$$WD = N_0 \cdot (1 + r_N)^t \times U_0 \cdot (1 - r_U)^t \quad (1)$$

$$r_N = d_{norm}(\mu_N, \sigma_N, a_{N,min}, b_{N,max}) \quad (2)$$

$$r_U = d_{norm}(\mu_U, \sigma_U, a_{U,min}, b_{U,max}) \quad (3)$$

where $WD$ is total water demand, $N_0$ is the initial population, $r_N$ is the population growth rate, $U_0$ is the initial WUPCD, and $r_U$ is the WUPCD decrease rate. Both $r_N$ and $r_U$ follow normal distributions (Eqs. (2) and (3), where $\mu$, $\sigma$, $a$, and $b$ are the mean, standard deviation, lower boundary, and upper boundary for the normal distribution. Both $r_N$ and $r_U$ are assumed to be statistically independent. A total of 10,000 samples were generated through Monte-Carlo simulation to support the analysis.

After computing the probability distribution of $WD$, the 1st, 50th, and 99th percentiles were selected to represent the best, median, and worst future water demand scenarios. Due to the randomness feature of the Monte Carlo simulation, the minimum and maximum values from the samples are usually sensitive to the sample size. Thus, the 1st and 99th percentiles are more suitable (and additionally, they can represent most of the uncertainty range of the simulation). The 1st percentile value represents we have a 99% confidence level that future water demand will be higher than this value. For convenient illustration, the

**Table 1**
List of the most severe droughts in the historical record and projected by GCMs. The 1950s drought was used as a baseline.

| | GCM | Start date | End date | Average P (mm/month) | Average T (°C) | Length (months) | Drought severity |
|---|---|---|---|---|---|---|---|
| 1950–1999 | Observation | 3/1/1954 | 11/30/1956 | 58.4 | 19.7 | 33 | 39.1 |
| 2000–2049 | CANESM2 | 12/1/2011 | 11/30/2013 | 47.8 | 20.2 | 24 | 58.1 |
| | CESM1-BGC | 7/1/2043 | 5/31/2045 | 65.1 | 20.5 | 23 | 15.8 |
| | CNRM-CM5 | 5/1/2043 | 2/28/2045 | 65.4 | 20.8 | 22 | 21.7 |
| | CSIRO-MK3-6-0 | 4/1/2022 | 5/31/2024 | 58.3 | 19.9 | 26 | 26.4 |
| | GFDL-ESM2M | 4/1/2030 | 11/30/2031 | 53.8 | 22.0 | 20 | 38.3 |
| | MIROC-ESM | 2/1/2013 | 10/31/2014 | 51.4 | 21.0 | 21 | 43.2 |
| | MPI-ESM-MR | 3/1/2037 | 12/31/2039 | 51.8 | 21.6 | 34 | 70.6 |
| | MRI-CGCM3 | 4/1/2005 | 7/31/2006 | 63.1 | 20.5 | 16 | 18.3 |
| 2050–2099 | CANESM2 | 1/1/2096 | 7/31/2097 | 46.4 | 25.6 | 19 | 48.3 |
| | CESM1-BGC | 7/1/2093 | 7/31/2095 | 62.5 | 23.7 | 25 | 46.0 |
| | CNRM-CM5 | 7/1/2074 | 3/31/2077 | 58.1 | 22.1 | 33 | 61.9 |
| | CSIRO-MK3-6-0 | 11/1/2075 | 8/31/2079 | 55.4 | 23.1 | 46 | 77.9 |
| | GFDL-ESM2M | 12/1/2091 | 12/31/2096 | 52.9 | 22.3 | 61 | 181.3 |
| | MIROC-ESM | 6/1/2088 | 12/31/2092 | 59.5 | 24.9 | 55 | 159.3 |
| | MPI-ESM-MR | 7/1/2093 | 9/30/2095 | 56.7 | 25.2 | 27 | 52.6 |
| | MRI-CGCM3 | 4/1/2071 | 5/31/2073 | 68.4 | 21.1 | 26 | 45.4 |

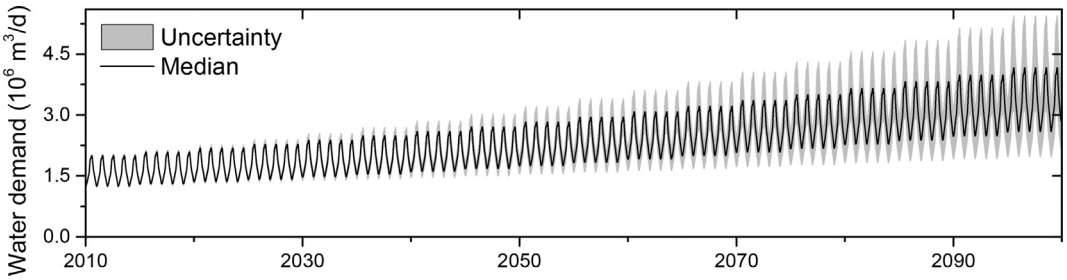


**Fig. 3.** Water demand projections from 2010 to 2099. The solid line shows the median value, and the shaded area shows the uncertainty (1st and 99th percentiles from Monte-Carlo simulations).

1st, 50th, and 99th percentiles are referred as the minimum, median, and maximum hereafter. Once the total water demand data for the entire City of Dallas for a future year is determined, it is distributed to the 7 reservoirs proportionally based on the historical water use pattern. Seasonal variation is prescribed based on the 5-year historical data from 2007 to 2011. Fig. 3 shows the continuous increase of total water demand (i.e., non-stationarity in water demand). The median water demand increases from $1.63 \times 10^6$ $m^3$/d in 2010 to $3.35 \times 10^6$ $m^3$/d in 2095. Along with the magnitude, the uncertainty range (the difference between minimum and maximum) is also increasing. In 2020, the uncertainty range is $1.32 \times 10^5$ $m^3$/d, which increases to $1.84 \times 10^6$ $m^3$/d in 2095.

### 3.3. Hydrological and water management simulations

As explained in the Introduction, a thorough understanding of the interplay between natural and managed water systems is critically lacking. This is because there are few distributed models that fully integrate natural hydrological processes and systematic water management practices. To close this knowledge gap, a newly developed model was employed in this study. The Distributed Hydrology Soil Vegetation Model with reservoirs (DHSVM-Res; Zhao et al., 2016b) is a physically-based fully-distributed model that has explicit reservoir operation functions incorporated (Fig. 4). Built upon the high spatial–temporal resolution DHSVM (Wigmosta et al., 1994), the model is suitable for investigating hydrologic regimes over heterogeneous domains under extreme events and/or a changing environment.

Specifically, DHSVM-Res has two features which are essential for studying integrated natural and managed water systems under conditions of non-stationarity. First, it explicitly represents the effects of urban land cover on hydrological processes using fractional impervious area and detention storage (Cuo et al., 2008). Second, the reservoir module is capable of simulating the management of a water system (e.g., multi-reservoirs) using either real or optimized operation rules (Zhao et al., 2016b). In-channel water withdrawals, reservoir storage withdrawals, reservoir water release, and return flows (e.g., flow from wastewater treatment plants) can be all simulated at their real-world locations within the model. In this study, we used historical monthly water use observations from TWDB and prescribed reservoir operation rules from the U.S. Army Corps of Engineers (for the water management simulations). Because most wastewater treatment plants for Dallas are located downstream of the simulated watersheds (Fig. 1), return flow is not included in this study.

The hydrological and water management simulations involved three steps. First, the DHSVM-Res model was calibrated and validated using historical observations, including streamflow station data and reservoir storage data from multiple locations. We simulated each of the 4 subbasins (Fig. 1) at a 200-meter resolution and a 3-hour time step using observed meteorological forcing data (Livneh et al., 2013). To focus on the non-stationarities of availability and demand, a fixed LULC map (i.e., National Land Cover Database 2006) was used. Because the urban growth is mostly located in the downstream regions of the study area

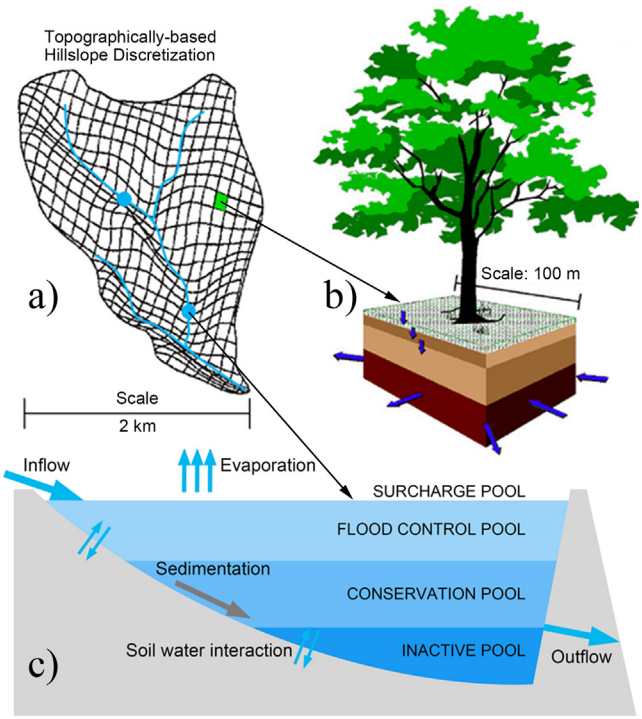


**Fig. 4.** Conceptual representation of DHSVM-Res which includes: (a) topographically based basin discretization in original DHSVM; (b) water movement for each grid cell; and (c) the integrated, multi-purpose reservoir with a flood control pool, a conservation pool, and an inactive pool (Zhao et al., 2016b).

(Fig. 1), impacts of LULC change on reservoir storage and supply reliability are very limited. The next step involved scenario simulations. The meteorological data during the selected drought events (Section 3.1) were used to drive DHSVM-Res. For each drought event, the reservoir release was calculated based on the projected water demand data. For example, the most severe drought projected for Period 1 by MPI-ESM-MR lasts from March 2037 to December 2039. Thus, the predicted water demand for this time period (Section 3.2) was used for the DHSVM-Res simulation associated with this drought event. In this study, the 1950s drought (from March 1954 to November 1956) was used as a baseline drought event. Because all reservoirs in the Dallas region were constructed after the 1950s drought, there was no corresponding water use data for this drought. Thus, we used three designed water demand scenarios (i.e. 2010, 2050, and 2090 water demand data) to take into account the uncertainty due to population and WUPCD changes. Outputs from Period 1 (2000–2049) and Period 2 (2050–2099) were compared with the baseline (1950s drought) to assess the long-term trend. Finally, several mitigation strategies to promote water supply resilience were tested using DHSVM-Res to identify the optimal solution for mitigating drought impact.

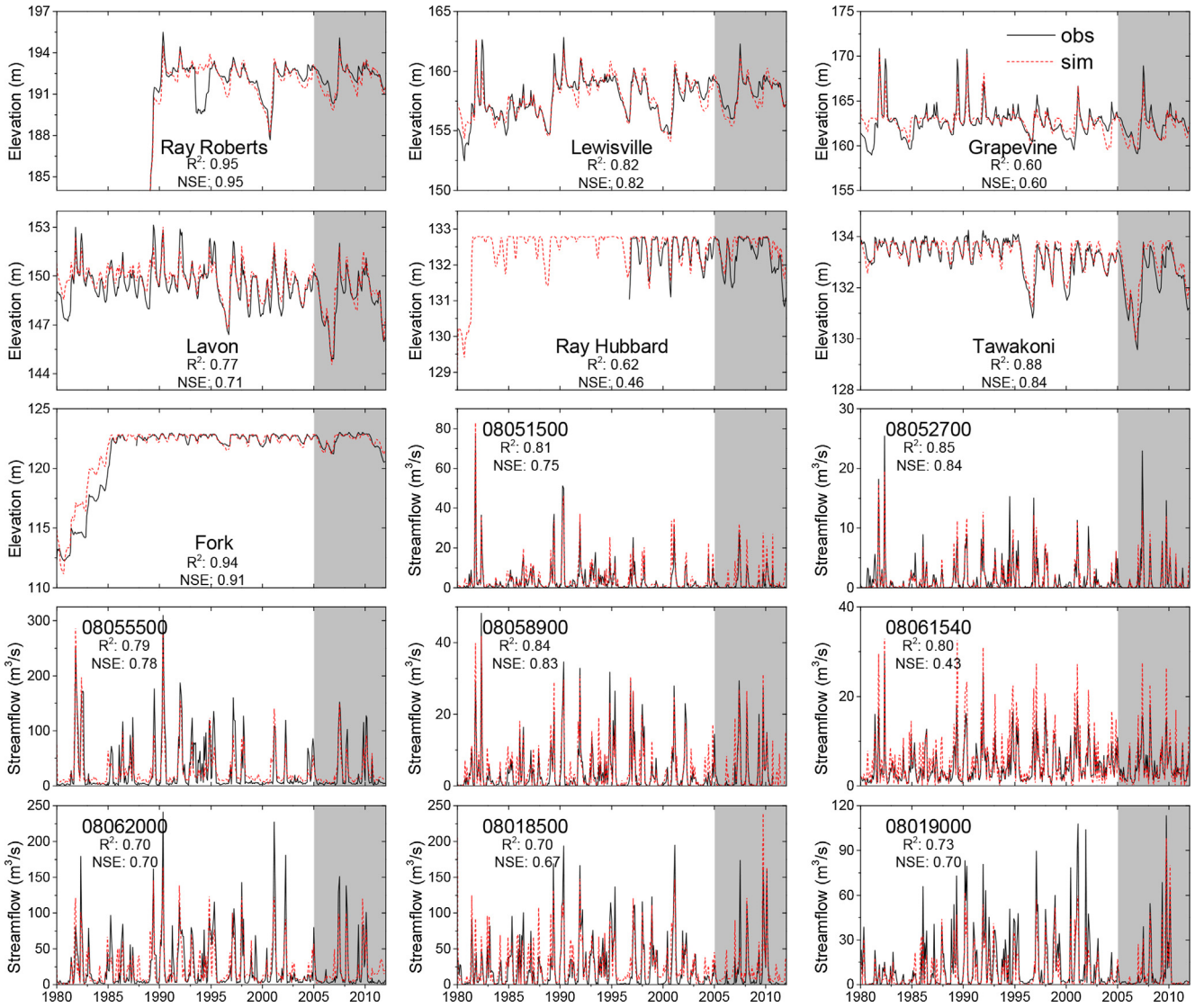


**Fig. 5.** Model calibration and validation results over 7 reservoirs and 8 streamflow gauge locations on a monthly scale. Shaded areas indicate the calibration period.

## 4. Results and discussions

### 4.1. DHSVM-Res calibration and validation

The model was calibrated from 2005 to 2011, and validated from 1980 to 2004 (Fig. 5). To best represent the subbasin hydrological processes and reduce the risk of overfitting, we chose to calibrate and validate for multiple streamflow monitoring locations. Based on data availability and watershed characteristics, 8 USGS gages were selected. The coefficient of determination ($R^2$) and the Nash-Sutcliff model efficiency (NSE) were used as the calibration criteria. Overall, the simulated outputs (including reservoir water elevation and streamflow) are in good agreement with the observed ones. For reservoir water elevation, the $R^2$ value ranges from 0.60 to 0.95 and the NSE ranges from 0.46 to 0.95. The low NSE for Ray Hubbard might be caused by the incomplete water use data. It is worth noting that the model can also capture the reservoir impoundment activities in an accurate manner, which can be useful for evaluating new reservoir operations. For streamflow simulations, the $R^2$ ranges from 0.70 to 0.85 and the NSE ranges from 0.43 to 0.84. These good levels of agreement benefit from the hyper-resolution and the explicit water management system simulations of DHSVM-Res.

### 4.2. Impacts of non-stationary water availability and demand on system supply resilience

Both reduced availability from multi-year drought events and increasing demand from population growth will significantly affect the water supply resilience. As discussed in detail in Sections 3.1 and 3.2, the hydrological model was used to simulate the water availability under future drought events extracted from a GCM ensemble, while Monte Carlo simulations were adopted to calculate the growing demand from population growth and WUPCD changes. To quantify the water supply resilience in Dallas, we employed two metrics: the relative storage and the water supply reliability. Because city planners manage the 7 reservoirs as a system to meet the water needs of the Dallas area, we evaluated these metrics for the system (rather than individual reservoirs). Thus, the relative storage is defined as the total storage divided by the total conservation storage over the 7 reservoirs in the study domain. Similarly, the water supply reliability is defined as the total water supply divided by the total water demand for each month. The overall supply reliability for a projected drought event is calculated by simply averaging the monthly values. Both metrics were shown as percentage values. To facilitate the analysis, we focused on the temporal evolution of the droughts with the assumption that the reservoir storage initial state is at the top of the conservation pool for every

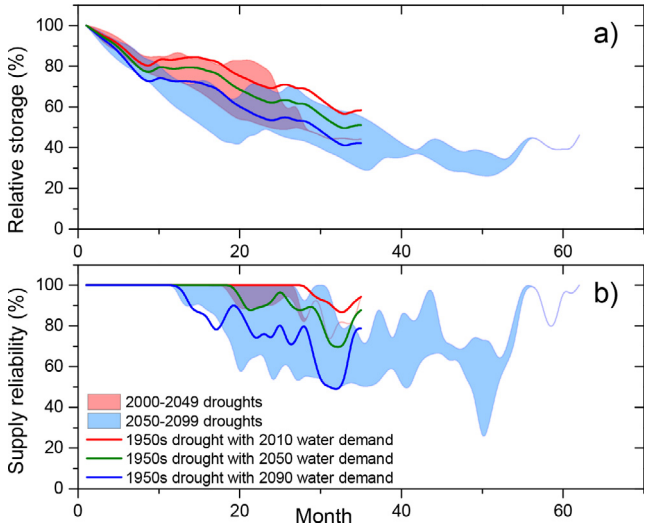


**Fig. 6.** Responses of (a) relative storage and (b) water supply reliability to the CMIP5 drought events (with the corresponding water demand) and the 1950s drought (with the 2010, 2050, and 2090 water demand). Storage and water supply are the summation of 7 reservoirs.

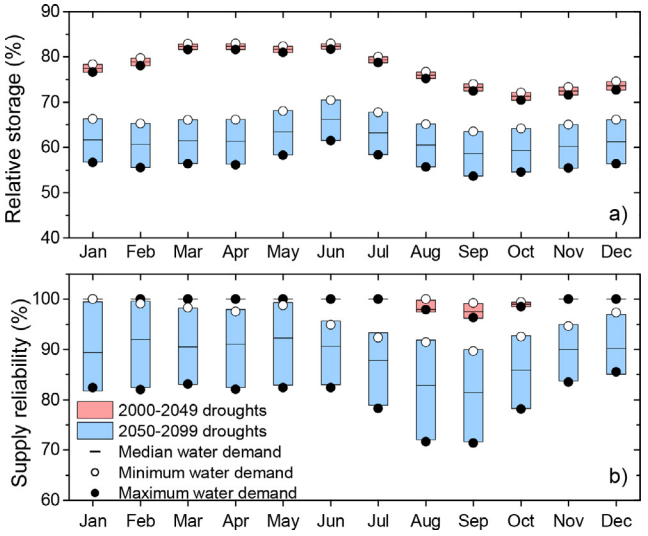


**Fig. 7.** Impacts of different water demand scenarios on (a) relative storage and (b) water supply reliability for each month. The water demand scenarios have minimum, median, and maximum values as indicated in Fig. 3.

reservoir at the beginning of each drought event.

Fig. 6a shows the relative storage from the ensemble of droughts during Period 1 and Period 2, as well as the relative storage from the 1950s drought under 2010, 2050, and 2090 demands. For these simulations, the corresponding median values of the projected water demand were used. Clearly, the average drought duration in Period 2 (36.25 months) is significantly longer than that in Period 1 (21.75 months). Due to the larger severity and longer duration, the average relative storage during a drought drops from 69.7% to 53.6% (16.1% difference) from Period 1 to Period 2.

Fig. 6b shows water supply reliability from the ensemble of droughts during the two periods. During Period 1, the reservoirs can still provide a sufficient amount of water to the city under severe drought. Water supply reliability for most droughts can maintain a level of 100%. Yet with respect to Period 2, the water supply reliability decreases dramatically due to both longer drought durations and larger water demand. During the first year of the drought, all of these 7 reservoirs can still maintain 100% supply reliability. However, the reliability value of one event drops to 26% after 50 months, which indicates that some potential extreme long-term droughts will cause devastating economic and ecological consequences. Comparing Period 1 with Period 2, the average water supply reliability during a drought drops from 95.9% to 81.7% (14.2% difference). There is also a significant difference in the first decision point (i.e., the first time water reliability drops under 100%) between Period 1 and Period 2. The median value for these 8 models decreases from 24 months to 14 months from Period 1 to Period 2. This decrease is mainly caused by water demand increase. For the 1950 s drought, the first decision point decreases from 29 months to 20 months to 13 months, as the water demand changes from the 2010 water demand to the 2050 demand to the 2090 demand. Typically, supply reliability is assessed under a worst case scenario associated with a return period, or under a large sample of events. In this study, we mainly focused on the most severe droughts (which are the worst scenarios that water managers are typically concerned with). Therefore, the reliability values are relatively low.

### *4.3. Uncertainties associated with the non-stationary water availability and demand*

Both sides of the non-stationarities – water availability and demand – involve considerable uncertainties. For the availability side, uncertainties can be attributed to climate models, greenhouse gas emission scenarios, downscaling methods, and hydrological models. Among these, uncertainties associated with GCM structures are generally the largest (Kay et al., 2009; Prudhomme & Davies, 2009a,b; Bennett et al., 2012). By choosing 8 GCM models, the uncertainties from different GCM structures can be represented in this study. On average, this uncertainty can result in a 13.3% variation of relative storage (Fig. 6a), and an 18.7% variation of supply reliability (Fig. 6b), for Period 2.

With respect to the demand side, primary sources of uncertainties include population growth rate and WUPCD change rate (Billings & Jones, 2011). The uncertainties from population growth and WUPCD changes can be represented using results from the Monte Carlo simulation (Fig. 3). Using the projected minimum/median/maximum water demands in DHSVM-Res, the seasonality of relative storage and supply reliability was generated (Fig. 7). Fig. 7 shows how these water demand uncertainties – represented by the minimum/median/maximum demand values (as shown in Fig. 3) – propagate to the DHSVM-Res simulated relative storage and supply reliability under the ensemble of drought events. For storage, clear seasonality can be observed, with September having the lowest value. This is mainly caused by high summer water consumption beginning in June. In addition, the high evaporation rate in the summer months also exacerbates the reservoir storage depletion. This lowest storage level also leads to the lowest supply reliability in the same month (Fig. 7b).

Compared to Period 1, Period 2 shows a much larger uncertainty range for both relative storage and water supply reliability. For example, the storage uncertainty range for September in Period 2 is 9% (from 54% to 63%) while it is 2% (72%–74%) in Period 1. Similar to the results in Fig. 6, supply reliability in Period 1 is always close to 100%, with the exception of August and September. Because the demand uncertainty during Period 1 is small, it has little effect on the storage and supply reliability. However, in Period 2, demand uncertainty will have a significant impact. The resultant uncertainty range of supply reliability in September for Period 2 is 19% (71%–90%).

As discussed above, both availability and water demand have notable uncertainties. Thus, it is essential to identify which of these parts plays a more dominant role with regard to water supply resilience. We compared the water resilience level (in terms of relative storage and reliability) driven by each GCM and water demand scenario (Fig. 8). For relative storage, the uncertainty range associated with GCMs is from 51% to 73%, while that from the increasing water demand is from

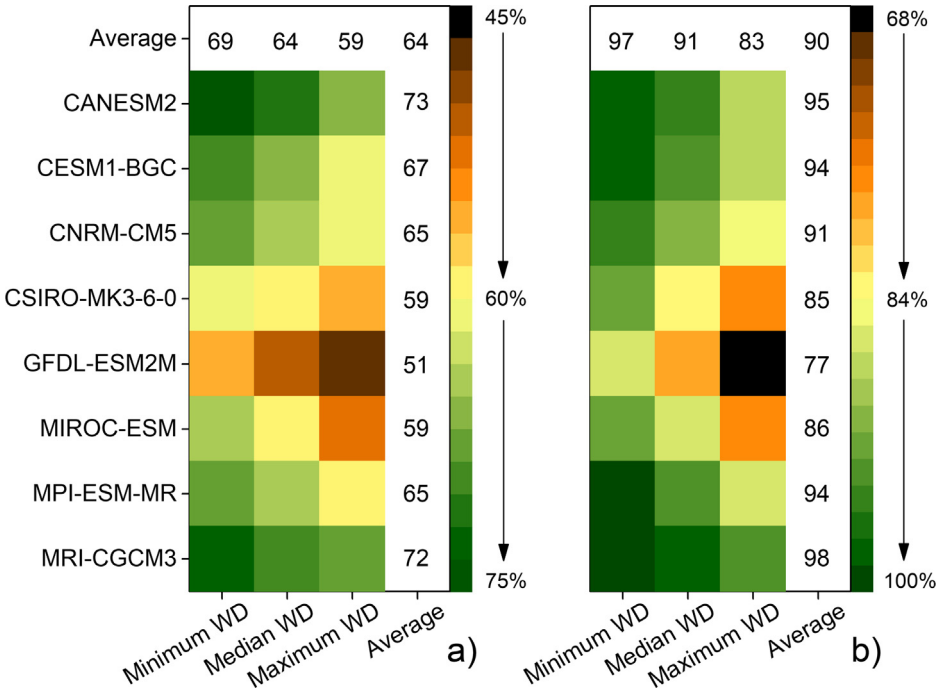


**Fig. 8.** a) Relative storage and b) supply reliability for each GCM and each water demand scenario for Period 2 (2050–2099). Each colored grid represents the average value during the drought projected by the selected GCM under a given water demand scenario. Each value to the right is the average of its corresponding row, while each value on the top is the average of the corresponding column.

59% to 69%. Water supply reliability is in the 77%–98% uncertainty range with GCMs, and the water demand uncertainty range is from 83% to 97%. In general, water availability non-stationarity shows a slightly larger uncertainty range. It is worth noting that these range values were calculated from an ensemble mean (averaged either from the 8 GCMs, or from the 3 demand scenarios). Because the study site for this research is the City of Dallas—one of the fastest growing large cities in the U.S.—the uncertainty range results from water demand non-stationarity are considerably significant. However, the GCM-based uncertainty is larger.

### 4.4. Mitigation strategy evaluations

In order to improve the water supply reliability, DWU has proposed several mitigation strategies such as additional conservation, integrating a new water source, and water use redistribution. In this study, the efficiency of these mitigation strategies was tested using DHSVM-Res:

(1) **Additional conservation**. Additional conservation mainly includes improving water use technology and reducing leakage and outdoor water use. The estimated saving percentage of total water use is 7% (TWDB, 2016). These additional conservation practices are proposed on top of the traditional conservation measures, especially during drought events. The traditional and long-term conservation measures (e.g., public awareness, policy intervention) were incorporated into the WUPCD projections ($r_U$ in Eq. (1), which tempers down the overall demand increase due to population growth.
(2) **Integrating a new water source**. Lake Palestine is a reservoir located in the nearby Neches River Basin, and is proposed to supply water to Dallas in the future. Palestine is estimated to be able to provide $3.86 \times 10^5\ m^3/d$ for DWU. However, the long distance to Dallas requires intensive construction of pipelines for water transfer.
(3) **Water use redistribution**. The current water use distribution among these reservoirs is based on the travel distance to the city, instead of the water availability (conservation storage) for each reservoir. For example, Lake Tawakoni has the largest conservation storage (which accounts for 23.8% of the total storage from the 7 reservoirs), yet it only contributes 10.9% of the total water supply. Redistributing the water use among these reservoirs based on reservoir storage can significantly improve the water supply reliability.
(4) **Combination strategy**. A combination of aforementioned 3 strategies was also tested.

We compared the efficiency of these strategies over the longest potential future drought projected from GFDL-ESM2M during Period 2 (i.e., the most extreme drought) with the business-as-usual scenario (i.e., no mitigation strategies). Fig. 9 shows that reservoir storage is continuously depleted during the drought for all of the strategies. The strategy by redistributing the water use shows the lowest relative storage. Consequently, even though more water can be supplied in the beginning, reliability will drop significantly around Month 50. Both additional conservation and new water source strategies show a slight increase of supply reliability. When all of these three strategies are combined, supply reliability shows the most improvement. The average supply reliability during the drought for business-as-usual is 77.8%, while it is 81.0%, 81.8%, 87.3%, and 93.7% for strategy 1 through strategy 4. These relative low reliability values are mainly caused by the chosen GCM (i.e., GFDL-ESM2M), which projects the worst drought in the future in this example demonstration. A non-parametric Kolmogorov-Smirnov Test was carried out to test whether the supply reliability is significantly improved using these strategies (as compared with the baseline run). P values for the tests (Fig. 9b) show that both redistribution and combined strategies can significantly improve the supply reliability. However, the redistribution strategy shows no improvement for the extreme condition (and has even worse supply reliability around Month 50). Therefore, compared with the individual strategies, the combined strategy is the most appropriate option to efficiently increase the water supply reliability.

There are two limitations worth noting in the strategy evaluations. First, we tested these strategies only based on hydrologic factors without considering economic factors, although we acknowledge that hydrologic evaluation needs to be complemented with economic analysis before supporting decision making. For example, an economic evaluation would allow for the design of a step-wise curtailment of the water supply as the drought intensifies in order to improve the water

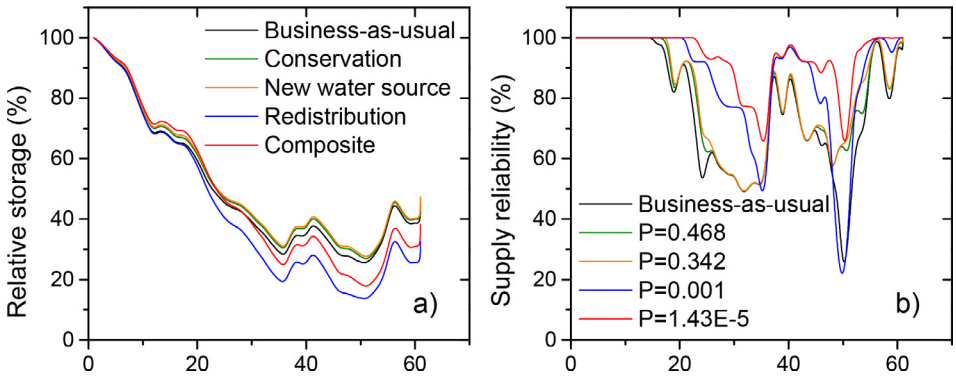


**Fig. 9.** Mitigation strategy evaluations by showing (a) relative storage and (b) supply reliability (using the longest potential future drought from GFDL-ESM2M as an example).

supply reliability in the long term and inform cost-benefit evaluation for additional infrastructure or contracts. Second, we used uniform mitigation strategies in a drought event. However, water managers might use adaptive management (changing strategies based on the strategy performance) in real world situations – which will improve supply reliability (Gao et al., 2016).

The representativeness of the results from this study is limited by several assumptions. First, we assumed that the initial reservoir level is at the top of the conservation pool at the onset of the drought. Although this makes the analysis straight forward, it tends to underestimate water stress. Another assumption is the simplified representation of the urban water demand (Eq. (1) based on population growth and WUPCD changes. However, other factors, such as economic development, drought specific increase in landscape water demand, water conservation and efficiency measures, can significantly affect our estimates (although population growth and WUPCD have the largest impact). Finally, Dallas fully depends on surface water, and therefore the groundwater contribution (less than 3% of total water supply; TWDB, 2016) was not considered in this study. However, techniques such as the managed aquifer recharge (MAR) method can help to store water in the underlying Trinity Aquifer system (Gao et al., 2014). Similar to the function of surface water reservoirs, the aquifer could help improving the supply reliability for Dallas in the future. In addition, groundwater should be incorporated in other study areas where it plays a significant part in the water supply system.

## 5. Conclusions

The resilience of water supply systems is affected by water availability and water demand, both of which are characterized with non-stationarity. In this study, by applying DHSVM-Res (which integrates detailed hydrology with water management operations) under selected multi-year drought scenarios in the City of Dallas, we quantified how the combined non-stationarity and uncertainties in multi-year drought severities and water demand growth will impact the future water supply resilience. Reduced availability is induced by the future droughts derived from GCM projections, and growing demand is calculated using Monte Carlo simulation by taking into account the population growth and WUPCD change uncertainties.

Using reservoir relative storage and water supply reliability as resilience metrics, the conclusions of this study are:

1) Both non-stationarities in water availability (associated with drought changes) and demand (associated with demand growth) have significant impacts on the water supply resilience. Droughts in Period 2 (2050–2099) are much more severe (with longer duration) than those in Period 1 (2000–2049). Consequently, water supply becomes less reliable in Period 2. With no curtailments or changes in operations, supply reliability could drop to 26% after a 4-year drought. The first decision point (at which reliability drops under 100%) decreases from 24 months to 14 months from Period 1 to Period 2.
2) Both uncertainties associated with availability and demand non-stationarity are large, and their combination affects the projected future water resilience estimates. For water availability, the primary source of uncertainties is GCM structure. In this study, it was found that the GCM model ensemble (which contains the 8 best performing models for drought simulation in the region) results in an average of 22% uncertainty range in relative storage and an average of 21% uncertainty range in supply reliability when taking Period 2 as an example. For water demand, the uncertainties are from population growth and WUPCD reduction, and result in a 10% range in relative storage and 14% in supply reliability. Over the second period, both uncertainties are of the same order of magnitude, which should further motivate water supply resources adequacy studies to explicitly consider both as none clearly dominates potential decision making.
3) None of the tested individual water management strategies (i.e., additional conservation, integrating a new water source, and water use redistribution) alone would be sufficient to significantly improve the water supply resilience for the City of Dallas under combined uncertainties in multi-year drought induced water availability decrease and population-growth induced water demand increase. A combination of these adaptation strategies is more appropriate for more robust long-term water supply resilience. With the feedback to water availability represented, this fully integrated framework can help inform economic analysis to select the best mitigation strategy.

This study demonstrates an end-to-end approach for evaluating water supply resilience under multiple sources of non-stationarity in an urbanized watershed. It bridges the gap between climate projections, demographic projections, high resolution hydrological modeling, water management operations, and best management practices. The current framework allows for representing water availability and associated uncertainties in space and time in a consistent manner (instead of deriving synthetic uncorrelated flow at each reservoir). The simulation results can be beneficial for the city managers to improve the water supply resilience, especially under extreme conditions.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhydrol.2018.05.037.

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